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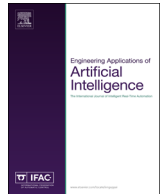
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Agent-based simulation of emergency response to plan the allocation of resources for a hypothetical two-site major incident

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ABSTRACT

During a major incident, the emergency services work together to ensure that those casualties who are critically injured are identified and transported to an appropriate hospital as fast as possible. If the incident is multi-site and resources are limited, the efficiency of this process is compromised as the finite resources must be shared among the multiple sites. In this paper, agent-based simulation is used to determine the allocation of resources for a two-site incident which minimizes the latest hospital arrival times for critically injured casualties. Further, how the optimal resource allocation depends on the distribution of casualties across the two sites is investigated. Such application supports the use of agent-based simulation as a tool to aid emergency response.

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1. Introduction

1.1. Pre-hospital response to major incidents

Pre-hospital response to a major incident covers the activities of the emergency services from initial deployment of resources up to the handing over of casualties to receiving hospitals (Lennquist et al., 2012). It involves multiple objectives such as 'saving and protecting human life', 'relieving suffering' and 'protecting property' (UK Cabinet Office, 2010). Different objectives may compete for the same resources, for example using firefighters to save and protect human life may divert them from protecting property leading to inevitable trade-offs. Even working towards a single objective may lead to competition between resources in the case of a multi-site incident. Making decisions to optimally trade-off competing objectives in emergency situations is an active area of research.

Towards achieving response objectives, standard procedures exist regarding what activities should be performed by the emergency services upon arrival at an incident site, and how these activities should be coordinated. For example, the 'Major Incident Medical Management and Support' (MIMMS) document (Advanced Life Support Group, 2011) describes how paramedics in the United Kingdom (UK) Ambulance Service should organize

themselves at the site through the creation of designated areas for performing certain tasks and the allocation of various 'operational' and 'tactical' level roles to manage these tasks. Similarly, there are documents describing how the UK Fire and Rescue Service manage incident sites (Great Britain, 2008; Skills for Fire and Rescue, 2013). The main documents detailing how the emergency services should respond to major incidents in the UK are indicated in Fig. 1.

'Saving and protecting human life' and 'relieving suffering' are two of the main objectives in emergency response. Therefore a major part of pre-hospital response is to identify and prioritize those casualties in need of treatment and/or transport to hospital. This is done by first locating casualties through search and rescue carried out by the Fire and Rescue Service, and then by triaging them which is performed by the Ambulance Service. Triage is the classification of a casualty into one of three categories to denote how urgent they require on-site treatment or transfer to hospital. Critically injured casualties requiring immediate attention are triaged as 'P1' ('immediate'). Casualties not critically injured whose treatment is required within 4 h are triaged as 'P2' ('urgent') whereas those whose treatment can safely be deferred beyond 4 h are referred to as 'the walking wounded' and are triaged as 'P3' ('delayed').

With response objectives in mind, a set of initial responses called 'predetermined attendances' (PDAs) have been designed as part of emergency preparedness in the UK (London Emergency Services Liaison Panel, 2012). PDAs are designed based on past experience of major incidents and expert knowledge of what

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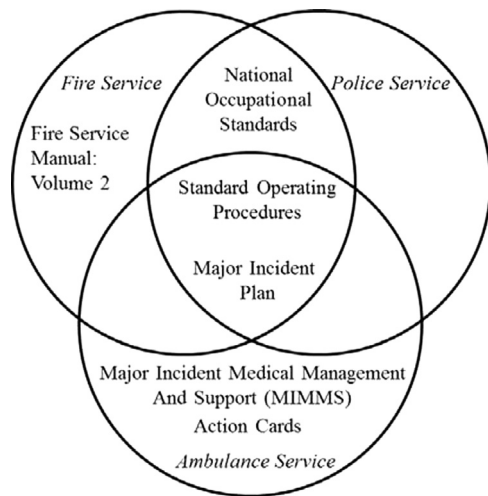


Fig. 1. The literature describing how the UK emergency services should respond to a major incident.

resources are likely to be needed in different circumstances depending on incident location and type, and personnel and equipment required (Hampshire Fire and Rescue Service, 2013). Despite the existence of PDAs, situations can still arise where insufficient resources exist to meet objectives, which are described as ‘uncompensated’ in the ambulance service (Advanced Life Support Group, 2011). Natural disasters are the most common cause of uncompensated incidents, however manmade incidents can also exceed the capacity of the emergency services. For example, coordinated terrorist attacks resulting in casualties distributed across multiple sites. When considering where to deploy resources, ‘it is necessary to prioritize limited resources among incidents’ (FEMA, 2010). Considering the case of allocating limited resources between multiple incident sites, a trade-off is required in response objectives between these sites. Emergency preparedness provides an opportunity to anticipate and consider these trade-offs, and design effective initial resource allocations for the early stages of uncompensated incidents to ensure that critically injured casualties are found and transported to hospital as quickly as possible.

1.2. Simulation of emergency response as part of preparedness

Live, table-top and discussion-based exercises are traditionally used to simulate emergency situations during emergency preparedness and planning (UK Cabinet Office, 2013). Further, this is done for the purposes of validating plans, testing procedures and training staff. However, computational tools provide a means to simulate emergency response and offer some unique advantages such as they allow investigations of ‘scenarios that would be prohibitively expensive, dangerous, environmentally damaging, or even physically impossible to re-create in reality’ (Straylight, 2010), and they ‘allow evaluation of alternative strategies to respond to a disaster event’ (Jain et al., 2003).

Agent-based simulation (ABS) is particularly well-suited to computer simulation of emergency response, due in part to its ability to provide a natural description of such situations (Bonabeau, 2002). In particular, the concept of an ‘intelligent agent’ (Wooldridge and Jennings, 1995), with its ability to act autonomously and proactively based on both its perception of its virtual environment and communication with other agents, is a natural way to model and simulate members of the emergency services during an emergency situation. However, Fiedrich and Burghardt (2007) point out that despite a number of research programmes in this area, it still remains an unadopted technology for emergency

preparedness and propose that the situation be improved incrementally through development of ‘basic applications for specific tasks’. More recently, Hoad and Watts (2012) confirm that ABS remains relatively unadopted for influencing policy (generally) and discuss what may be done to improve the situation.

1.3. Contribution of this paper

The research presented in this paper is aimed at determining an optimized initial emergency response to a hypothetical two-site incident using an ABS, called STORMI (‘Simulation of the Tactical and Operational Response to Major Incidents’), which has been developed to include a greater level of detail than seen previously in terms of the aspects of response modeled coupled with the behaviors modeled within agents representing a range of first responders. Further, the ABS developed uses Ordnance Survey MasterMap™ Geographic Information System (GIS) files (Ordnance Survey, 2015) enabling a virtual geographical environment of any region of the UK to be created thus providing the flexibility to model major incidents in any location. By applying the ABS to a particular hypothetical two-site incident, the paper aims to determine (1) how the allocation of resources affects the time taken for all critically injured casualties (triaged as P1) to be transported from each site to hospital, and thus identify the ‘best’ allocation of resources based on the minimum overall arrival time of a critically injured casualty at hospital; (2) how the ‘best’ allocation of resources changes as the distribution of critically injured casualties between the two sites varies. In determining (1) and (2), it is acknowledged that the results presented in this paper relate to a particular hypothetical case study. In order to generalize the results, further work would need to be undertaken such as that suggested in the conclusion of this paper.

The remainder of the paper is organized as follows. Section 2 provides a brief summary of existing ABSs for emergency response which are most closely related to that developed as part of the research reported in this paper. In Section 3 an overview is presented of the STORMI ABS developed to solve the resource allocation problem referred to earlier. Section 4 defines a hypothetical two-site incident to which STORMI is applied to determine an optimized allocation of resources. In Section 5 results of the experiments carried out are presented and discussed. Finally, Section 6 concludes the paper and offers some suggestions for future work.

2. ABS for emergency response

The application of ABS to emergency response began in the late 1990s. Specifically, the annual RoboCup Rescue simulation competition was found in 1999, which was motivated by the 1996 Kobe Earthquake (Kitano et al., 1999). Competitors are required to design behaviors for fire, ambulance and police service agents with the aim of maximizing an amalgamated ‘score’ reflecting the health of casualties and damage to property in a city, e.g. Marsella et al. (2001), Skinner and Barley (2006), Iwata et al. (2008), and Chou et al. (2009). RoboCup Rescue has been described as being ‘concerned with designing smart algorithms, not with investigating a current human social system as it exists and designing a public policy for it.’ Carley et al. (March 2006). Given its focus on normative behavior, RoboCup Rescue and other ABSs of this nature are of limited relevance to the work presented in this paper which, instead, is aimed at modeling descriptive behavior. Thus, the brief summary to follow of ABS for emergency response focuses on work most closely related to that developed in this research, specifically involving agents exhibiting descriptive behavior. For a more comprehensive review of the usage and implementation of

ABS for emergency response, the reader is referred to [Hawe et al. \(2012a\)](#).

SimGenis enables the evaluation of French emergency rescue plans in generic large-scale crisis situations ([Saoud et al., 2004, 2005, 2006](#)). Autonomous agents defined as victims or rescuers (doctors, nurses, firemen, and managers) are represented in a virtual incident site consisting of a grid of cells, categorized as normal, obstacle or danger. Victim agents are inanimate and reactive in that they exhibit a continuously evolving degree of health according to five heuristic rules depending on their location, and the rescuers' intervention and treatment. Rescuer agents' behavior is modeled according to 14 heuristic rules relating to site exploration for victims, on site treatment, victim transfer to advanced medical posts and evacuation to hospital, ambulance routings, and the management of centralized and distributed rescue. Simulation experiments involved either a centralized decision making rescue strategy with the incident site considered as one zone or a distributed decision making rescue strategy with the incident site considered as four zones, in combination with communication via paper forms or electronic devices. For each simulation, seven configurations were used with between 73–200 victims in various states of health and 35–150 rescuers. In all simulations, the assessment criteria used were minimize global evacuation time and maximize rescue rate. A finding of this work is reported as there being no 'best' rescue plan since this depends on the disaster configuration.

Planning with Large Agent Networks against Catastrophes (PLAN-C) is a stochastic agent based model for urban disaster simulation and emergency planning ([Narzisi et al., 2007](#)) and has been used to simulate and evaluate variations of a hypothetical Sarin attack on Manhattan island in New York City ([Narzisi et al., 2006](#)) and a food poisoning outbreak in Minas Gerais, Brazil ([Gill et al., 2005](#)). PLAN-C's GIS-based environment is represented as a graph with nodes signifying particular locations including hospitals. Within the environment, an agent can represent a person, an onsite treatment unit, an ambulance, a hospital, and the catastrophe itself. Based on a Sarin gas attack simulation involving 1000 people, 22 hospitals and 5 onsite responder units, a number of relationships involving mortality rate have been established ([Narzisi et al., 2006](#)). These include relationships between the number of fatalities and (i) person behavior including health level at which a person goes to hospital, and degree of worry and level of obedience, (ii) hospital behavior such as resource level, and decisions at which health level to discharge a person, and (iii) the rate which people are updated with hospital information.

The Autonomous Robots for Observation of Urban Networks after Disasters (AROUND) project involved the development of an ABS which mimics the ambulance response during post-earthquake scenarios in Vietnam ([Chu et al., 2009](#)), and has been proposed to help decision makers involved in search and rescue in developing countries ([Boucher et al., 2009](#)). A rescue model, based on the GAMA (GIS and Agent based Modeling Architecture) platform ([Amouroux et al., 2009](#)), has been developed to provide an environment for simulations. In this model, buildings, hospitals and ambulances are represented as agents, in addition to fire fighters, police officers and victims. As an example, ambulance agents exhibit certain behaviors and follow decision strategies to minimize loss of life including determining choices such as which casualty an ambulance will collect and to which hospital they should be taken. These strategies are based on the agent's local view of the situation and, thus, can be sub-optimal. However, an expert can intervene, via an interactive interface, if he/she identifies a better course of action for an ambulance agent. Based on such interventions, the agents can acquire expert knowledge using adapted machine learning algorithms leading to new decision strategies, which can be used in similar future situations.

CrisisCoordSim is an ABS for investigating different crisis response coordination mechanisms in the Netherlands, specifically hierarchically mediated coordination and autonomous mutual adjustment ([Gonzalez 2009a; b](#)). The ABS couples a discrete-event simulation environment with an agent-based model of the response organization, which includes agents representing firemen and medics along with their respective commanders. Thirty-two scenarios were defined by combinations of number of civilians, firemen and medics, allied with mechanisms for rescue coordination (mediation and mutual adjustment) and assignment coordination (mediated or autonomous assignment of firemen) ([Gonzalez, 2010](#)). Each scenario response was measured in terms of effectiveness and coordination cost with the former consisting of response time, number of civilians affected and number of fatalities, and the latter being the volume of messages exchanged among agents within and between the fire and medical services. Based on an analysis of the experimental results, a series of insights were offered in relation to the impact of the configuration of coordination mechanisms on the response metrics being assessed.

3. Overview of the design and implementation of an ABS

In this section, an overview is presented of the design and implementation of an ABS, called STORMI, which is based on official UK emergency response literature. This ABS provides a contribution in terms of the level of detail of the aspects of response modeled coupled with the behaviors of agents for 17 different emergency first responders. Further, in terms of implementation, the ABS developed uses Ordnance Survey MasterMap Geographic Information System (GIS) files (Ordnance Survey, 2015) such that a virtual geographical environment of any region of the UK can be constructed thus providing the flexibility to model major incidents in any location.

3.1. Design of agents

Including an appropriate level of detail in an agent-based model is important if it is to engage practitioners and be of potential use to them. Discussions with practitioners from the emergency services and emergency planning units regarding response led to the identification of much of the literature referred to in [Fig. 1](#). Further, these discussions revealed that practitioners' expectations of agent-based models of emergency responders, in addition to the aspects of response to be modeled in an ABS, would involve significantly more detail than existing ABSs offered. [Table 1](#) lists the fundamental aspects of the response to be modeled from the perspective of the UK ambulance service and fire service, and an indication of which of these aspects is accounted for in the four ABSs focused on in [Section 2](#) along with that developed in this research, namely STORMI. Although taken from UK plans, many of the aspects referred to exist in other countries as reported in documents such as MIMMS ([Advanced Life Support Group, 2011](#)). [Table 1](#) also indicates some implementation aspects of ABSs.

To meet the expectations of practitioners and avoid the ABS developed being too abstract, which is cited as a reason why ABSs are not used in practice ([Hoad and Watts, 2012](#)), an aim of this work was to capture as many of the aspects of emergency response listed in [Table 1](#) within the agent-based models of each of the main individual roles in the emergency services. Several architectures exist as potential templates for building agents. Although aiming to model human individuals as agents, cognitive architectures ([Chong et al., 2007](#)) such as ACT-R ([Anderson, 1983](#)), Soar ([Wray et al., 2006](#)) and CLARION ([Sun, 2006](#)) go far beyond

Table 1
The level of detail in ABSs of emergency response.

ABS	Aspects of response modeled										Implementation		
	Ambulance service						Fire Service						
	Incident control point	Casualty clearing station	Primary and secondary triage	Hospital triage	Air Ambulance hospital transport	Non-ambulance hospital transport	Sectorization	Search and rescue	Extrication	Fire-fighting	GIS topography (e.g. buildings)	Road network	Multiple levels of detail
SimGenis	x	✓	✓	x	x	x	x	✓	x	x	x	✓	x
PLAN-C	x	x	x	✓	x	x	x	x	x	x	x	✓	x
AROUND	x	x	x	x	x	x	x	x	x	x	x	✓	x
CrisisCoordSim	✓	✓	x	x	x	x	x	✓	x	✓	x	x	x
STORMI	✓	✓	✓	✓	✓	✓	✓	✓	✓	x	✓	✓	✓

Table 2
The tactical and operational level roles related to UK major incident response for which FSMs were designed.

Ambulance service	Fire service	Police service
<i>Tactical level</i>		
Ambulance Incident Commander	Fire Incident Commander	Police Incident Commander
<i>Operational level</i>		
Ambulance Communications Officer	Fire Communications Officer	Police Communications Officer
Parking Officer	Sector Commander	Survivor Reception Area Officer
Primary Triage Officer		
Forward Control Officer		
Casualty Clearing Officer		
Secondary Triage Officer		
Ambulance Loading Officer		
<i>Operative level</i>		
Paramedic	Firefighter	Police Officer

what was required in this work (Gilbert and Sun, 2006). Architectures at a more suitable level of abstraction, and have already been used to model emergency responders' behavior, include Belief-Desire-Intention (BDI) (Pereira et al., 2011), utility functions and decision trees (Chu et al., 2009), genetic programs (Runka, 2010) and Finite State Machines (FSMs) (Gonzalez, 2009a). However, some of these architectures are more suitable for designing agents with normative, as opposed to descriptive, behaviors. It is argued here that FSMs are appropriate for the agent-based models developed in this work given that an emergency responder performs one of a finite number of activities at any one time, which is captured in a FSM only being able to be in one state at any particular time. Also, an emergency responder changes what they are doing (their state) due to an event, specifically (1) the perception of something of interest in the environment, (2) receiving a message from another individual, or (3) completing their current activity. Also, a benefit of using FSMs is that they have an intuitive visual representation, namely the Unified Modeling Language state machine diagram (Gomaa, 2011).

Using the literature referred to in Fig. 1, a separate FSM was designed for each of the 17 different roles listed in Table 2. One of these roles, namely the Primary Triage Officer, is selected here for illustrative purposes to show the process of mapping behavior of individuals to a FSM. All other FSMs were constructed following the same process as described for this role. Fig. 2 shows the FSM designed for the Primary Triage Officer, which is based entirely on Action Card 5 (North East Ambulance Service, 2010) as shown in Fig. 3. The annotations on states shown in Fig. 2 denote which part of the literature they rely on (AC 5.x denotes paragraph x on Action Card 5). On being allocated the role by the Ambulance Communications Officer, the Primary Triage Officer moves to the area

designated by the Ambulance Incident Commander (AC 5.3) then enters a default state 'Coordinating Triage Sieve'. Transitions from this state are as follows:

1. If a casualty is seen, the Primary Triage Officer goes to him/her and performs triage sieve ('Sieving Casualty'); if the casualty requires first aid then their position is recorded.
2. If another responder is seen, and there is a casualty requiring first aid, then the Primary Triage Officer directs the responder to the casualty ('Tasking Responders').
3. Every T seconds (a parameter to be set) the Primary Triage Officer sends a message to the Forward Incident Officer updating them on the number of casualties found ('Updating Forward Incident Officer').

With a FSM for each of the 17 different roles listed in Table 2, the corresponding agents were implemented within the ABS.

3.2. Implementation of the ABS

STORMI is an ABS developed to simulate the response by the UK's emergency services to major incidents, which can potentially be spread over multiple sites (Hawe et al., 2012c). It comprises three main components: the Scenario Designer allows users to set up a hypothetical single or multi-site incident anywhere in the UK using Ordnance Survey MasterMap's™ Topography Layer and Integrated Transport Network™ Layer; the Simulator enables the response to this incident to be simulated; the Response Designer permits the user to design the predetermined attendances defining which resources go to each incident site during the simulation. Here, a brief overview is presented of STORMI's Simulator, which

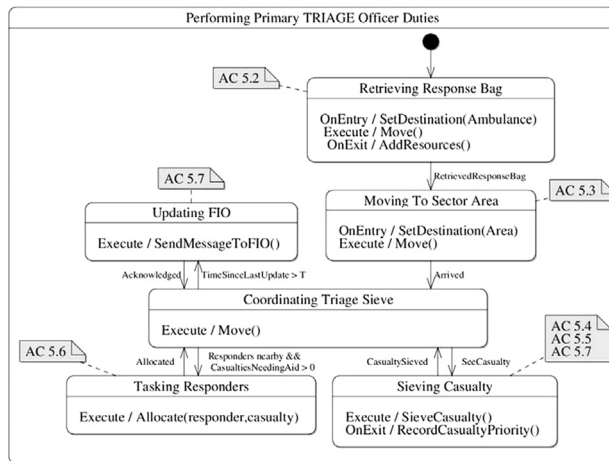


Fig. 2. FSM for the Primary Triage Officer.

includes agents representing first responders. For further details, the reader is directed to Hawe et al. (2012b,c). As shown in Fig. 4, STORMI's Simulator is composed of three separate programs which communicate along the lines indicated: a *Global Simulator* simulates all activity outside the incident sites (e.g. resources travelling from resource bases to incident sites); an *Incident Site Simulator* simulates all activity inside a single incident site (and so multiple instances run for a multi-site incident); a *Control Centre Simulator* simulates decisions taken at the Emergency Operations Center.

3.2.1. Incident site simulator(s)

Environment: The environment in each Incident Site Simulator represents the geographical area around an incident site. It is constructed using Ordnance Survey MasterMap vector GIS files (Ordnance Survey, 2015), which is one of the highest resolution vector GIS products available in the UK. More specifically, the Topography Layer is used to provide information on individual buildings and the Integrated Transport Network™ Layer provides information on the road network. This is the environment in which the agents perceive, move around and perform actions.

Agents: Following the approach in Buckland (2005), the FSMs were implemented as agents in the Incident Site Simulator. Thus, the agents in the Incident Site Simulator represent the emergency services at the human individual level (although when travelling in a vehicle in the Incident Site Simulator, the vehicle is represented as an agent).

3.2.2. Global simulator

Environment: The environment is modeled as a road network, using the Integrated Transport Network™ Layer, but displayed using raster GIS images. Resource bases (ambulance stations, fire stations, police stations, air ambulance stations, and hospitals) are based at certain nodes of the network as set up by the user in the Scenario Designer.

Agents: Individuals from the emergency services are aggregated into vehicle agents in this program given that while they are travelling in the Global Simulator's environment these vehicle agents can only perform the task 'travel to or from an incident site'. However, casualties are still modeled at an individual level as they are transported from the incident site to hospitals by ambulance and air ambulance. When deployed to an incident site from their resource base following a query from the Control Center Simulator, vehicle agents travel along the road network towards the site. On arriving at the site, vehicle agents are disaggregated into individual emergency responder agents in the Incident Site

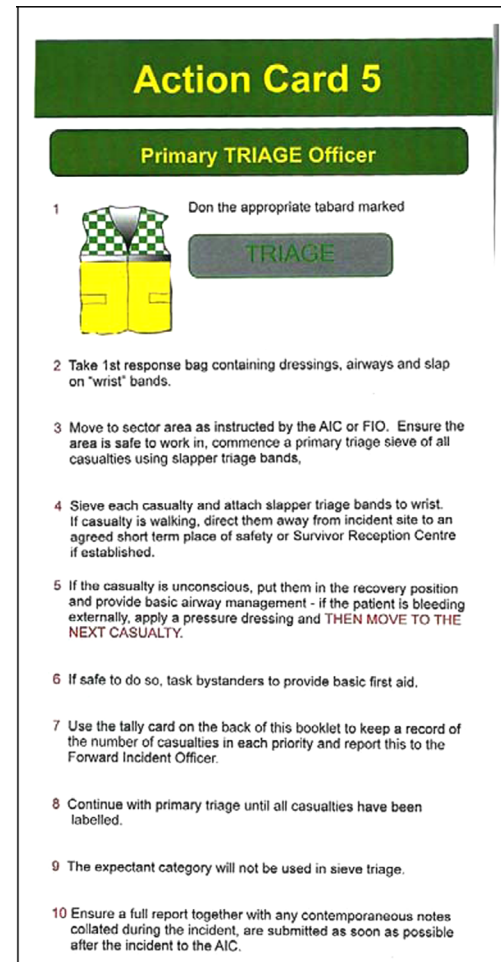


Fig. 3. Action card for Primary Triage Officer. Reproduced with permission from North East Ambulance Service (2010).

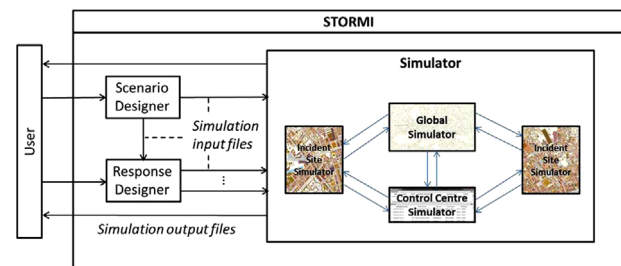


Fig. 4. The STORMI environment.

Simulator (and thus are removed from being modeled as aggregated vehicle agents in the Global Simulator) where, as individuals, they are able to perform a range of tasks according to the FSM corresponding with their particular role.

3.2.3. Control Centre simulator

This program receives calls from casualties and/or members of the public at each incident site. Based on call information, and on user-defined predetermined attendances (London Emergency Services Liaison Panel, 2012), it determines how many resources should be deployed. Also, it queries each resource base in the Global Simulator about the availability of resources so that the specific resources to be deployed can be identified. This information is then

communicated to the appropriate resource bases resulting in the deployment of the requested resources to the incident site(s).

4. Case study: hypothetical two-site incident

In this section, a case study of a hypothetical two-site incident is defined. The results of applying STORMI to this case study are then presented and discussed in Section 5.

4.1. Incident location

The incident involves a number of casualties at two sites in the North-East of England: Gateshead Interchange is an underground metro station approximately 1 mile south of Newcastle-upon-Tyne; Royal Quays is an outlet shopping center in North Shields approximately 8 miles east of Newcastle-upon-Tyne. Both these locations are busy areas with large numbers of people passing through each day. According to the 2012 UK Risk Register (UK Cabinet Office, 2012), 'attacks on crowded spaces' and 'attacks on transport' are two of the three likeliest types of malicious attacks facing the UK in the next five years (the other being 'cyber-attacks'), and so these were deemed reasonable target sites for the hypothetical case study.

4.2. Emergency services' resources

4.2.1. Locations

The fire and rescue stations, ambulance stations and hospitals in the vicinity of the incident sites are listed in Table 3 and their locations are shown in Fig. 5. Furthermore, the fire and rescue stations were identified from the Tyne & Wear Fire and Rescue website (TWFRS, 2013) whereas the ambulance stations were identified from a response to a Freedom of Information request (FOI.12.029) (NEAS, 2012). The number of resources (fire engines/ambulances) available at each resource base was based on the size of each base.

Table 3
Available resources at the fire stations and ambulance stations labeled in Fig. 5.

Fire and Rescue Stations		
NCN	Newcastle North	2
NCS	Newcastle South	2
NCE	Newcastle East	2
GHN	Gateshead North	2
GHE	Gateshead East	2
STW	South Tyneside West	3
STE	South Tyneside East	2
NTE	North Tyneside East	3
NTS	North Tyneside South	2
Ambulance Stations		
MLA	Market Lane Ambulance Station	2
SHA	Sheriff Hill Ambulance Station	4
NDA	Netherby Drive Ambulance Station	2
SRA	Sandyford Road Ambulance Station	4
DGA	Debdon Gardens Ambulance Station	4
HHA	Hadrian Hospital Ambulance Station	2
HLA	Hawkey's Lane Ambulance Station	2
PHA	Parkside House Ambulance Station	2
BLA	Boldon Lane Ambulance Station	2
Hospitals		
RVI	Royal Victoria Infirmary	
QEH	Queen Elizabeth Hospital	
STH	South Tyneside Hospital	
NTH	North Tyneside Hospital	

4.2.2. Allocations

In this case study, 20 fire engines and 24 ambulances are available for use. For the resource bases that are in much closer proximity to one of the incident sites than the other, it is more obvious to which incident site they should deploy resources. However, two fire stations and two ambulance stations may be identified that could arguably dispatch resources to either site due to being approximately equidistant from either site. These are Newcastle East Fire Station (NCE), South Tyneside West Fire Station (STW), Sandyford Road Ambulance Station (SRA) and Debdon Gardens Ambulance Station (DGA).

Three different allocations for the fire engines are investigated, denoted by FE_{GH8} , FE_{GH10} and FE_{GH12} , the full details of which are given in Table 4. Briefly, the differences between these three allocations are as follows:

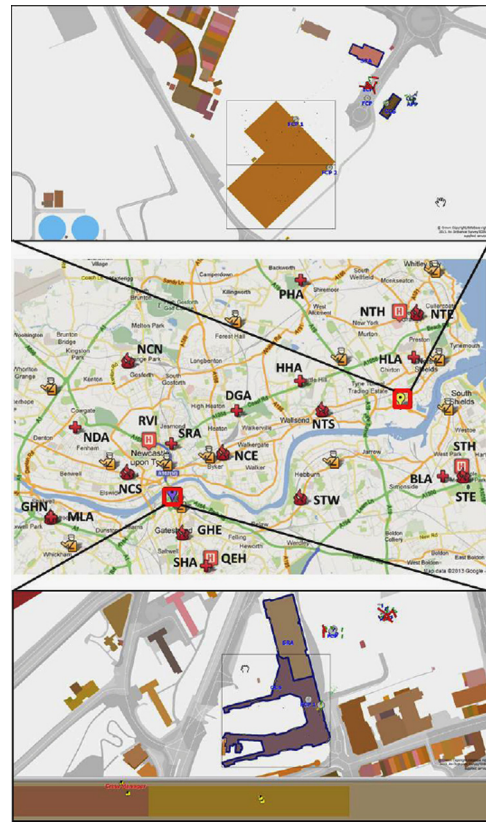


Fig. 5. The ambulance stations, fire stations and hospitals used in the response.

Table 4
Three possible allocations of fire engines to Gateshead Interchange (GH) and Royal Quays (RQ).

	FE_{GH8}		FE_{GH10}		FE_{GH12}	
	GH	RQ	GH	RQ	GH	RQ
NCN	2	0	2	0	2	0
NCS	2	0	2	0	2	0
NCE	0	2	2	0	2	0
GHN	2	0	2	0	2	0
GHE	2	0	2	0	2	0
STW	0	3	0	3	2	1
STE	0	2	0	2	0	2
NTE	0	3	0	2	0	2
NTS	0	2	0	2	0	2
Total	8	12	10	10	12	8

- FE_{GH10} : The two fire engines at NCE are dispatched to Gateshead Interchange and the three fire engines at STW are dispatched to Royal Quays.
- FE_{GH8} : As FE_{GH10} , but with the two fire engines at NCE dispatched to Royal Quays.
- FE_{GH12} : As FE_{GH10} , but with two of the fire engines at STW dispatched to Gateshead Interchange.

Similarly, three different allocations for the ambulances are investigated, denoted by AMB_{GH10} , AMB_{GH12} and AMB_{GH14} , the full details of which are presented in Table 5. The differences between these three allocations are summarized as follows:

- AMB_{GH12} : The four ambulances at SRA are dispatched to Gateshead Interchange and the four ambulances at DGA are dispatched to Royal Quays.
- AMB_{GH10} : As AMB_{GH12} , but with two of the four ambulances at SRA dispatched to Royal Quays.
- AMB_{GH14} : As AMB_{GH12} , but with the two of the four ambulances at DGA dispatched to Gateshead Interchange.

Combining these three possible ways to allocate fire engines and three possible ways to allocate ambulances yields nine different allocation strategies in total, RA1–RA9, as indicated in Table 6.

4.3. Casualties

4.3.1. Distribution between two sites

Eleven different casualty distributions are considered, C1–C11, as listed in Table 7. At the Royal Quays site, casualties are located inside a building, at ground level. At the Gateshead Interchange site, casualties are located in an underground metro tunnel, 21 m below ground level. The total number of critically injured casualties across both sites (triaged as P1) is fixed at 20; however the number of critically injured at each site differs in each distribution. Also, the number of P2 casualties at each incident site is fixed at 5 in each distribution. The presence of P2s is important due to the existence of *overtriage* which acts to divert resources from

Table 5

Three possible allocations of ambulances to Gateshead Interchange (GH) and Royal Quays (RQ).

	AMB_{GH10}		AMB_{GH12}		AMB_{GH14}	
	GH	RQ	GH	RQ	GH	RQ
MLA	2	0	2	0	2	0
SHA	4	0	4	0	4	0
NDA	2	0	2	0	2	0
SRA	2	2	4	0	4	0
DGA	0	4	0	4	2	2
HHA	0	2	0	2	0	2
HLA	0	2	0	2	0	2
PHA	0	2	0	2	0	2
BLA	0	2	0	2	0	2
Total	10	14	12	12	14	10

Table 6

The nine resource allocation strategies RA1 – RA9.

	AMB_{GH10}	AMB_{GH12}	AMB_{GH14}
FE_{GH8}	RA1	RA2	RA3
FE_{GH10}	RA4	RA5	RA6
FE_{GH12}	RA7	RA8	RA9

Table 7

The 11 different casualty distributions C1–C11.

	GH		RQ	
	P1s	P2s	P1s	P2s
C1	5	5	15	5
C2	6	5	14	5
C3	7	5	13	5
C4	8	5	12	5
C5	9	5	11	5
C6	10	5	10	5
C7	11	5	9	5
C8	12	5	8	5
C9	13	5	7	5
C10	14	5	6	5
C11	15	5	5	5

casualties who really are critically injured, thus delaying their arrival time at hospital.

4.3.2. Hospital allocation and arrival times

Four hospitals are available for use in the case study, however hospital allocation is not under investigation and so is kept constant. At the Gateshead Interchange site, casualties triaged as P1 are sent to the Queen Elizabeth Hospital (QEH) whereas casualties triaged as P2 are sent to the Royal Victoria Infirmary (RVI). At the Royal Quays site, casualties triaged as P1 are sent to North Tyneside Hospital (NTH) and casualties triaged as P2 are sent to South Tyneside Hospital (STH).

In this case study, the time taken for the final critically injured casualty from each site to arrive at hospital is of interest. The times taken for the final critically injured casualty to arrive at hospital from the Gateshead Interchange site and the Royal Quays site are denoted as T_{GH} and T_{RQ} respectively. These arrival times are recorded directly from the ABS which is run in real time. That is, the arrival times correspond with the point in time during the real time simulation when the final seriously injured casualty arrives at each hospital.

4.4. Formulation of the optimization problem

Based on the information presented in the preceding subsections, the case study can be formally framed as an optimization problem. For each casualty distribution $C \in \{C1, C2, \dots, C11\}$, find the resource allocation $R \in \{R1, R2, \dots, R9\}$ which minimizes $T = \max\{T_{GH}, T_{RQ}\}$. Thus, the design variable is the resource allocation strategy, while the casualty distribution acts as a control variable. The objective function is the final hospital arrival time of a critically injured casualty.

5. Results

5.1. Experiments

To solve the optimization problem formulated in Section 4.4, STORMI has been used as a means of determining the objective in each experiment undertaken, namely the final hospital arrival times of critically injured casualties from each incident site. Prior to presenting results, the experiments conducted are defined in relation to the case study presented in Section 4.

Simulations have been carried out of the response by the emergency services, as defined in Table 3, to a major incident with casualties distributed across two incident sites, Gateshead Interchange and Royal Quays. Recall Table 3 indicates the available resources at a specified number of Fire and Rescue stations,

Ambulance stations and hospitals in the vicinity of these two incident sites. The 11 casualty distributions, C1–C11, considered are as defined in Table 7, which for each distribution indicates the number of critically injured casualties requiring immediate attention, P1, and those not critically injured but whose treatment is required within 4 h, P2. Table 6 defines the nine resource allocation strategies, RA1–RA9, each of which indicates the number of fire engines and ambulances sent to the two incident sites.

Given 9×11 different resource-allocation/casualty-distribution combinations were considered, and each of these combinations was run multiple (21) times, then a total of 2079 experimental runs were conducted. Each experiment was run until the final critically injured, P1, casualty from each site arrived at hospital.

5.2. Discussion

Table 8 shows the median (10th out of 21) final hospital arrival times (in seconds) of a critically injured casualty from each site for each resource-allocation/casualty-distribution combination. Median values are presented for each combination as these map explicitly to a particular simulation response, whereas mean values do not. Viewing the results in a multi-objective manner, where the final critically injured casualty hospital arrival time from both sites need to simultaneously be minimized, yields a set of Pareto-optimal results indicated in bold. The solution to the single-objective problem (where the overall final critically injured casualty hospital arrival time needs to be minimized) is indicated with an asterisk (*).

For illustrative purposes, with regard to the casualty distribution C1, Fig. 6 shows the associated information presented in Table 8 with dominated and Pareto-optimal results identified. Furthermore, for this casualty distribution, Fig. 6 indicates the best solution in terms of minimizing the latest hospital arrival time of the final critically injured casualty from either of the two incident sites.

In relation to the single-objective problem indicated earlier, Table 9 maps each of the 11 casualty distributions to the resource allocation strategy which yields the best overall result. Note that

Table 8

Median last arrival times of P1 casualties at hospital from Gateshead Interchange (top entry in each cell) and Royal Quays (bottom entry in each cell). Pareto optimal resource allocations for each casualty distribution are in bold, whilst overall best for each casualty distribution is denoted by an asterisk.

	RA1	RA2	RA3	RA4	RA5	RA6	RA7	RA8	RA9
C1	3598* 3576*	3213 4796	3168 6301	3602 4550	2973 4730	2958 6246	3602 4521	2910 4697	2729 6221
C2	3700 3431	3514 4709	3298 6266	3606* 3456*	3539 4739	2987 6197	3714 4551	3594 4633	2955 6197
C3	3960 3521	3641 4651	3554 6205	3664* 3337*	3634 4664	3173 6199	3704 3373	3617 4631	3101 6141
C4	4100 3478	3828 4566	3628 4746	3843 3422	3715* 3361*	3565 4779	3832 3434	3696 4594	3610 4734
C5	4248 3454	4016 3493	3716 4734	4007 3349	3676* 3446*	3639 4711	3852 3271	3743 3527	3617 4649
C6	4964 3320	4146 3339	3838 4710	4923 3275	3937 3327	3683 4641	4996 3272	3799* 3308*	3747 4677
C7	5098 3250	4235 3389	4109 4671	5007 3243	4151 3407	3764 4606	5055 3218	4037* 3246*	3791 4635
C8	5086 2938	4483 3085	4135 3117	5103 3097	4198 2873	3988 3202	5063 3032	4055 3202	3874* 3219*
C9	5376 2840	4640 3020	4284 3106	5230 2863	4297 2898	4040 2898	5209 2833	4202 2928	4011* 2874*
C10	5626 3142	4966 3156	4409 3148	5326 3057	4948 3056	4141 3102	5248 2983	5060 3093	4094* 3068*
C11	5700 2152	5060 3179	4533 3232	5562 2320	5001 3132	4229 3183	5409 2192	5038 3096	4154* 3179*

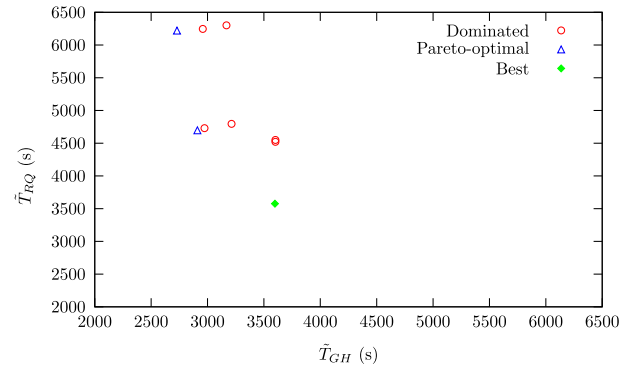


Fig. 6. Median last hospital arrival times for P1 casualties, for casualty distribution C1.

Table 9

Overall best resource allocations for the 11 casualty distributions C1–C11.

	AMB _{GH10}	AMB _{GH12}	AMB _{GH14}
FE _{GH8}	C1	–	–
FE _{GH10}	C2, C3	C4, C5	–
FE _{GH12}	–	C6, C7	C8, C9, C10, C11

Table 9 should be considered together with Table 6 in Section 4. For example, strategy RA8, which corresponds to FE_{GH12} and AMB_{GH12}, is the best allocation of resources for casualty distributions defined by C6 and C7. As detailed in Section 4, recall that RA8 corresponds to a response from the emergency services involving 12 and 8 fire engines being allocated to the incident sites at Gateshead Interchange and Royal Quays respectively, coupled with 12 ambulances being assigned to each of the two incident sites.

The results in Table 9 agree with intuition. The overall best resource allocation for C1, where 75% of the P1 casualties are at Royal Quays, is the one which sends most resources to Royal Quays, namely RA1 (AMB_{GH10}–FE_{GH8}). As the proportion of P1s at Gateshead Interchange increases, the optimal resource allocation changes to allocations which increasingly send more resources to Gateshead Interchange (as one would expect), but it is interesting to note the exact path of the optimal resource allocation through the discrete resource-allocation space (represented by cells in Table 9). Table 9 shows that the way in which these optimal allocations change is that it first becomes advantageous to send additional fire engines to Gateshead Interchange (RA4 is optimal for C2 and C3). Further increases in the proportion of P1s at Gateshead Interchange (C4 and C5) require additional ambulances only (RA5). As the proportion of P1s at Gateshead Interchange increases again further (C6 and C7) it becomes advantageous to now send further additional fire-engines (RA8). Finally, further increases in the proportion of P1s at Gateshead Interchange result in the resource allocation which sends most resources to Gateshead Interchange becoming optimal (RA9).

Given the possible resource allocations available, these results for the two extreme casualty distributions (C1 and C11) may have been guessed intuitively prior to running experiments. However, predicting the optimal resource allocations for the remaining casualty distributions is more difficult, and this is where the value of ABS may be greatest in emergency planning.

While median values have been used in this discussion of results, it has been observed that the use of mean values, which do not correspond to a particular simulation response, reveal the same pairings of best resource allocations to nine of the 11 of the casualty distributions. In two cases, namely for the casualty distributions C3 and C5, the best resource allocation are RA7 (rather than RA4) and RA8 (rather than RA5) respectively.

However, it is noted that for C3 the difference in seconds between the resource allocation strategies RA7 and RA4, and for C5 the difference between RA8 and RA5, is approximately 0.4% and 1% respectively. Further, for C3 and C5, the respective resource allocations mentioned have the same allocation of ambulances to both incident sites and only differ in the number of fire engines.

6. Conclusion and summary

Multiple response objectives exist during a major incident. In a multi-site incident involving a number of casualties, each incident site has its own demand for resources and set of objectives. If the resources of the emergency services are limited, decisions must be made regarding how these should be allocated across the multiple sites to best serve the objectives at each site. This is not a trivial task as trade-offs will inevitably exist and no single allocation of resources will be 'best' from the viewpoint of every site.

Emergency preparedness provides an opportunity to anticipate such trade-offs in a response, and design resource allocations which are at least Pareto-optimal, i.e. the best possible given the competition for resources from each site. These allocations ensure that no improvement in objectives may be made at one site without a detriment in objectives at another; in particular, for each Pareto-optimal allocation there is no other allocation which dominates it (i.e. is strictly better in one objective and no worse in the others). From these Pareto-optimal allocations, one may be selected to be implemented based on an overall viewpoint of the incident.

In this paper, an ABS has been used to carry out a series of experiments for a particular case study, namely a hypothetical two site incident in the North East of England, with each experiment involving varying resource allocations and casualty distributions between the sites. For each site, one response objective was set: the hospital arrival time of the final critically injured casualty from that site.

Results obtained followed a trend that agrees with common sense and intuition, i.e. the higher the proportion of critically injured casualties at an incident site, the higher the proportion of resources should be allocated to that site. However, although this trend may be obvious, it is not trivial to determine exactly how the resource allocation should change as the proportion of casualties at one site gradually increases relative to those at the other site. Using ABS has enabled these trends to be quantified for the particular case study considered, which may assist emergency planners to justify resource allocations used in situations with limited resources.

Further work: An area for further work would be the application of the ABS presented in this paper to case studies involving a range of different geographical locations with multiple site incidents and a greater number of injured people, and emergency calls being received from many people in various locations. In this paper a particular hypothetical major incident involving two incident sites has been considered. The effect of varying the distribution of casualties between the two sites was investigated, however the results remain tied to the specifics of the case study. In order to generalize the results, a possible route forward would be to parameterize the case study further. For example, the relative locations of the two incident sites and the distances of each resource base from to each site could be varied. In addition, the effect of the number of incident sites and the geographical location of these sites could be investigated. Methods from DACE (Design and Analysis of Computer Experiments) (Santner et al., 2003) and more generally machine learning could then be used to design experiments for the purpose of constructing a 'metamodel' (Kleijnen et al., 2005) of the ABS. Such a metamodel would provide

a computationally inexpensive tool to allow researchers to investigate, for example, how interactions between various parameters which define a major incident can influence the optimal response to that incident. Early work in this area of research has been performed in e.g. Gonzalez (2010), however there remains much scope for further development.

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References

- Advanced Life Support Group, 2011. Major Incident Medical Management and Support: The Practical Approach at the Scene, 3rd ed. Wiley-Blackwell.
- Amouroux, E., Chu, T., Boucher, A., Drogoul, A., 2009. GAMA: an environment for implementing and running spatially explicit multi-agent simulations. In: Lecture Notes in Artificial Intelligence, vol. 5044, pp. 359–371.
- Anderson, J.R., 1983. The Architecture of Cognition. Harvard University Press, Cambridge.
- Bonabeau, E., 2002. Agent-based modeling: methods and techniques for simulating human systems. Proc. Natl. Acad. Sci. 99, 7280–7287.
- Boucher, A., Canal, R., Chu, T., Drogoul, A., Gaudou, B., Le, V., Moraru, V., van Nguyen, N., Vu, Q., Taillandier, P., et al., 2009. The AROUND project: adapting robotic disaster response to developing countries safety. In: IEEE International Workshop on IEEE Security & Rescue Robotics (SSRR), pp. 1–6.
- Buckland, M., 2005. Programming Game AI by Example. Wordware Publishing, Inc., Plano, Texas.
- Carley, K.M., Fridsma, D.B., Casman, E., Yahja, A., Altman, N., Chen, L.-C., Kaminsky, B., Nave, D., 2006. BioWar: scalable agent-based model of bioattacks. IEEE Trans. Syst. Man Cybern. Part A: Syst. Humans 36 (March (2)), 252–265.
- Chong, H.-Q., Tan, A.-H., Ng, G.-W., 2007. Integrated cognitive architectures: a survey. Artif. Intell. Rev. 28, 103–130.
- Chou, W.Y.J., Marsh, L., Gossink, D., 2009. Multi-agent coordination and optimisation in the RoboCup Rescue project. In: 18th World IMACS/MODSIM Congress. Cairns, Australia (July).
- Chu, T., Drogoul, A., Boucher, A., Zucker, J., 2009. Interactive learning of independent experts criteria for rescue simulations. J. Univ. Comput. Sci. 15 (13), 2701–2725.
- FEMA, 2010. IS-703.A: NIMS Resource Management (January). (<http://training.fema.gov/EMIWeb/IS/courseOverview.aspx?code=is-703.a>).
- Fiedrich, F., Burghardt, P., 2007. Agent-based systems for disaster management. Commun. ACM 50 (3), 41–42.
- Gilbert, N., 2006. When does social simulation need cognitive models?. In: Sun, R. (Ed.), Cognition and Multi-Agent Interaction. Cambridge University Press, Cambridge, pp. 428–432 (Chapter 19).
- Gomaa, H., 2011. Software Modeling and Design: UML, Use Cases, Patterns, and Software Architectures. Cambridge University Press.
- Gonzalez, R.A., 2009a. Analysis and design of a multi-agent system for simulating a crisis response organization. In: Barjis, J., Kinghorn, J., Ramaswamy, S., Dubois, E., Johannesson, P. (Eds.), Proceedings of the EOMAS Workshop Held in Conjunction with CAISE'09 Conference. Amsterdam, The Netherlands (June).
- Gonzalez, R.A., 2009b. Crisis response simulation combining discrete-event and agent-based modeling. In: Landgren, J., Jul, S. (Eds.), Proceeding of the Sixth International ISCRAM Conference. Gothenburg, Sweden (May).
- Gonzalez, R.A., 2010. A Framework for ICT-Supported Coordination in Crisis Response (Ph.D. thesis). Delft University of Technology.
- Great Britain: H.M. Fire Service Inspectorate, 2008. Fire Service Manual, vol. 2: Fire Service Operations Incident Command, 3rd ed. Stationery Office, London.
- Hampshire Fire and Rescue Service, 2013. Community Response: Pre-determined Attendances. (<http://www.hantsfire.gov.uk/incidenttypes>).
- Hawe, G.I., Coates, G., Wilson, D.T., Crouch, R.S., 2012a. Agent-based simulation for large-scale emergency response: a survey of usage and implementation. ACM Comput. Surv. 45, 1, Article 8.
- Hawe, G.I., Wilson, D.T., Coates, G., Crouch, R.S., April 2012b. STORMI: an agent-based simulation environment for evaluating responses to major incidents in the UK. In: Rothkrantz, L., Ristvej, J., Franco, Z. (Eds.), Proceedings of the Ninth International Information Systems for Crisis Response and Management (ISCRAM) Conference, Vancouver, Canada.
- Hawe, G.I., Wilson, D.T., Coates, G., Crouch, R.S., 2012c. The STORMI Scenario Designer: a program to facilitate setting up agent-based simulations of major

- incident emergency response. In: Yan, L., Hong, C., Wenzhang, L. (Eds.), *Proceedings of the Third IEEE International Conference on Emergency Management and Management Sciences (ICEMMS 2012)*, IEEE, Beijing, China, pp. 648–651 (August).
- Hoad, K., Watts, C., 2012. Are we there yet? Simulation modellers on what needs to be done to involve agent-based simulation in practical decision making. *J. Simul.* 6 (1), 67–70.
- Iwata, K., Ito, N., Toda, K., Ishii, N., 2008. Analysis of agents' cooperation in robocuprescue simulation. *Stud. Comput. Intell.* 149, 227–236.
- Jain, S., McLean, C., 2003. A framework for modeling and simulation for emergency response. In: Chick, S., Sánchez, P.J., Ferrin, D., Morrice, D.J. (Eds.), *Proceedings of the 2003 Winter Simulation Conference*, pp. 1068–1076.
- Kitano, H., Tadokoro, S., Noda, I., Matsubara, H., Takahashi, T., Shinjou, A., Shimada, S., 1999. RoboCup Rescue: Search and rescue in large-scale disasters as a domain for autonomous agents research. In: *Proceedings of IEEE International Conference on Systems, Man, and Cybernetics*, 1999, vol. 6 (October).
- Kleijnen, J.P.C., Sanchez, S.M., Lucas, T.W., Cioppa, T.M., 2005. State-of-the-art review: a user's guide to the brave new world of designing simulation experiments. *INFORMS J. Comput.* 17 (3), 263–289.
- Lennquist, S., Dobson, R., 2012. The prehospital response. In: Lennquist, S. (Ed.), *Medical Response to Major Incidents and Disasters - A Practical Guide for All Medical Staff*. Springer, Berlin Heidelberg, pp. 33–61 (Chapter 3).
- London Emergency Services Liaison Panel, 2012. LESLP Major Incident Procedure Manual, 8th ed. TSO (The Stationery Office).
- Marsella, S., Tambe, M., Adibi, J., Al-Onaizan, Y., Kaminka, G.A., Musela, I., 2001. Experiences acquired in the design of robocup teams: a comparison of two fielded teams. *Auton. Agents Multi-agent Syst.* 4, 115–129.
- Mysore, V., Gill, O., Daruwala, R., Antonioti, M., Mishra, B., Saraswat, V., 2005. Multi-agent modeling and analysis of the brazilian food poisoning scenario. In: Macal, C., North, M., Sallach, D. (Eds.), *Proceedings of the Agent 2005 Conference on Generative Social Processes, Models, and Mechanisms* (October).
- Mysore, V., Narzisi, G., Mishra, B., 2006. Agent modeling of a sarin attack in Manhattan. In: *Proceedings of the First International Workshop on Agent Technology for Disaster Management*. Hokkaido, Japan, pp. 108–115 (May).
- Narzisi, G., Mincer, J., Smith, S., Mishra, B., 2007. Resilience in the face of disaster: accounting for varying disaster magnitudes, resource topologies, and (sub) population distributions in the PLAN-C emergency planning tool. In: *Lecture Notes in Computer Science*, vol. 4659, p. 433.
- NEAS, 2012. FoI Request—Station Addresses (April). (http://www.neas.nhs.uk/media/45923/foi.12.029_-_response_letter.pdf).
- North East Ambulance Service, UK, 2010. Major Incident & CBRN Action Cards (September).
- Pereira, A.H., Nardin, L.G., Brand, A.A.F., Sichman, J.S., 2011. LTI agent rescue team: a BDI-based approach for Robocup Rescue. In: *Proceedings of RoboCup 2011*, Istanbul.
- Runka, A., 2010. Genetic Programming for the RoboCup Rescue Simulation System (Master's thesis), Faculty of Computer Science, Brock University, St. Catharines, Ontario (September).
- Santner, T.J., Williams, B.J., Notz, W., 2003. *The Design and Analysis of Computer Experiments*. Springer, New York.
- Saoud, N.B.-B., Dugdale, J., Pavard, B., Ahmed, M.B., Mena, T. B., Touai, N.B., 2004. Towards planning for emergency activities in large-scale accidents. In: *Proceedings of ISCRAM*, Brussels (May).
- Saoud, N.B.-B., Mena, T.B., Dugdale, J., Pavard, B., Ahmed, M.B., 2006. Assessing large scale emergency rescue plans: an agent based approach. *Int. J. Intell. Control Syst.* 11 (4), 260–271.
- Saoud, N.B.-B., Pavard, B., Dugdale, J., 2005. An agent-based testbed for simulating large scale accident rescue heuristics. *J. Comput. Sci. Spec.*, 21–26, Issue.
- Skills for Fire and Rescue, 2013. National occupational standards (<http://www.skillsforjustice-ipds.com/nos/>).
- Skinner, C., Barley, M., 2006. Robocup rescue simulation competition: status report. In: *Lecture Notes in Computer Science*, vol. 4020, pp. 632–639.
- Straylight, 2010. The Emergency Simulation Program (ESP). (<http://www.straylighttmm.com/>).
- Sun, R., 2006. The CLARION cognitive architecture: extending cognitive modeling to social simulation. In: Sun, R. (Ed.), *Cognition and Multi-Agent Interaction*. Cambridge University Press, Cambridge, pp. 79–99 (Chapter 4).
- TWFRS, 2013. Tyne and Wear Fire and Rescue Service. (<http://www.twfire.gov.uk/>).
- UK Cabinet Office, 2010. Responding to Emergencies, The UK Central Government Response: Concept of Operations (March). (<http://www.cabinetoffice.gov.uk/media/349120/conops-2010.pdf>).
- UK Cabinet Office, 2012. National Risk Register of Civil Emergencies.
- UK Cabinet Office, 2013. Emergency Exercises. (<https://www.gov.uk/emergency-planning-and-preparedness-exercises-and-training>).
- Wooldridge, M., Jennings, N.R., 1995. Intelligent agents: theory and practice. *Knowl. Eng. Rev.* 10 (2), 115–152.
- Wray, R.E., Jones, R.M., 2006. Considering soar as an agent architecture. In: Sun, R. (Ed.), *Cognition and Multi-Agent Interaction*. Cambridge University Press, Cambridge, pp. 53–78, Chapter 3.